PUCs, these mechanisms typically contain explicit profit "sharing" provisions if the actual rate-of-return exceeds a predetermined limit (Braeutigam and Panzer (1993)). Profit sharing mechanisms could also be implicit in the FCC form of price-cap regulation. In fact, high profits due to the increased efficiency of British Telecom under price-cap regulation in the U.K. and prices below the price-cap led to a revision of the price-cap formula toward a more binding cap (Kwoka (1993)).

The specific form of price-cap regulation adopted for AT&T divided services into three "baskets" depending on the perceived level of competition in the service. "Basket 1" includes residential and small business services, international services and operator assisted and calling card services; "Basket 2" is limited to 800 number services; and "Basket 3" contains all remaining services, principally those offered to large businesses. Each basket has its own price-cap, and sometimes a floor, that increases with inflation and decreases with a productivity factor and "exogenous" changes in costs, mainly carrier access charges. As services have been shown to be competitive, they have been removed from price-cap regulation. In October 1991, the FCC permitted contract carriage for AT&T's offerings to large business customers. However, AT&T must publish a summary of the contract and offer the same price to similarly situated customers (Griboff (1992)). Similarly, almost all 800 services were removed from Basket 2 in May 1993 with the introduction of 800 number portability.[2] This study uses prices from Basket 1, thought to be less competitive than the other baskets.

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[2]800 number portability allows a customer to keep its 800 telephone number when it changes long distance companies. Since companies make investments specific to a telephone number (e.g.,advertisements, printed material), switching costs arise if the number must be forfeited. See also Kaserman and Mayo (1991).

III. Empirical Methodology

This study attempts to measure the degree of market power as the difference between price and marginal cost. In theory, a profit maximizing firm not facing price regulation will set prices such that the price markup over long-run marginal costs, its Lerner index, is equal to the absolute value of the inverse of the firm's own-price demand elasticity. Thus, the degree of market power can be inferred from estimates of this elasticity. However, the data and methodological requirements for the estimation of firm specific demand elasticities are extremely demanding. This section describes the methodology employed to estimate demand elasticities for AT&T and the OCCs and to infer price markups over marginal cost.

A. Two-level budgeting

Long distance service can be somewhat differentiated across firms. For high-volume business customers and those who use data transmission services, there may be substantial variation in product attributes. Even for residential and small business customers, differences in, for instance, perceived quality, customer service, and billing systems could render long distance services heterogeneous across firms. Finally, some carriers offer lower quality, lower priced, non-premium service, although its popularity has diminished considerably. Despite the foregoing differences, it is not unreasonable to aggregate different firms' long distance service into a single market that is distinct from outside goods. In this way, it is possible to disentangle the decisions regarding the amount of long distance service to consume and the firm chosen to provide it.

A two-level budgeting approach is used to estimate the demand system (Deaton and Muellbauer (1980)). The upper level determines the industry-wide demand for long distance, while the lower level determines how demand is allocated among the various firms in the market. This approach is used because it accords with perceptions of the long distance market, and it partially separates the effects of general industry price reductions from price differences among firms within the industry. Real prices for long distance service fell by about 50% between 1984 and 1991. Differences among firms' prices were much smaller throughout this period. Two-level budgeting is also supported by the observation that, while real total expenditures on all toll service increased by only 3.5% between 1984 and 1991, the market shares of individual firms changed considerably.

With two-level budgeting, consumers are assumed to allocate funds across different broad commodities (level one) and then distribute the allocated funds among the specific goods within the commodity group (level two). In the upper-level, demand for aggregate long-distance service is determined based on a price index for the industry,

$$Q_D^{LD} = Q_D^{LD}(P^{LD}, P^{Loc}, P^{Set}, Y)$$

where Y represents total income and P^{LD}, P^{LOC}, and P^{Set} represent the prices of long distance service, local telephone service and telephone sets respectively. The total expenditures on long distance service is determined as a function of price,

$$Y^{LD} = P^{LD} Q_D^{LD}(P^{LD}, P^{Loc}, P^{Set}, Y)$$

where Y^{LD} represents income allocated to the long distance commodity group in the upper level.

In the lower level, consumers choose which long distance carrier's service to purchase based on their relative prices and Y^{LD}, the amount of income budgeted to long distance service,

$$Q_D^1 = Q_D^1(P^1, P^2, P^3, \dots, P^N, Y^{LD}). \tag{1}$$

Equation (1) looks like a traditional demand equation where quantity demanded is a function of prices and "income." Traditional demand elasticities are calculated by differentiating equation (1) with respect to firm 1's price, P^1. The partial derivative introduces two terms because firm 1's price is implicit in long distance expenditures,

$$\frac{\partial Q^1}{\partial P^1} = \frac{\partial Q^1}{\partial Y^{LD}}\frac{\partial Y^{LD}}{\partial P^1} + \left.\frac{\partial Q^1}{\partial P^1}\right|_{Y^{LD}}.$$

This equation can be expressed in elasticity form by multiplying both sides by P^1 / Q^1,

$$\eta_{11} \equiv \frac{P^1 \partial Q^1}{Q^1 \partial P^1} = \frac{Y^{LD} \partial Q^1}{Q^1 \partial Y^{LD}}\frac{P^1 \partial Y^{LD}}{Y^{LD} \partial P^1} + \left.\frac{P^1 \partial Q^1}{Q^1 \partial P^1}\right|_{Y^{LD}}. \tag{2}$$

The second term in equation (2) above is the elasticity conditional on the amount of income budgeted to long distance, η^C_{ii}. The first term represents the "income" effect due to changes in the amount of income allocated to long distance service from changes in the price of good 1. The first part of the first term, $Y^{LD}\ \partial Q^1 / Q^1\ \partial Y^{LD}$, is analogous to an "income" elasticity for the good, ϵ^C_1. If income elasticities do not differ much across long distance companies, the value of this lower-level income elasticity will be close to one. The second part of the first term, $P^1\ \partial Y^{LD} / Y^{LD}\ \partial P^1$, can be modified as follows:

$$\begin{aligned}
\frac{P^1 \partial Y^{LD}}{Y^{LD} \partial P^1} &= \frac{P^1}{Y^{LD}}\frac{\partial (P^{LD} Q^{LD})}{\partial P^1} \\
&= \frac{P^1}{Y^{LD}}\left[Q^{LD}\frac{\partial P^{LD}}{\partial P^1} + P^{LD}\frac{\partial Q^{LD}}{\partial P^1}\right] \\
&= \frac{P^1}{Y^{LD}}\left[Q^{LD}\frac{\partial P^{LD}}{\partial P^1} + P^{LD}\frac{\partial Q^{LD}}{\partial P^{LD}}\frac{\partial P^{LD}}{\partial P^1}\right] \\
&= \frac{P^1}{Y^{LD}}\left[Q^{LD}\frac{Q^1}{Q^{LD}}\left(1 + \frac{P^{LD} \partial Q^{LD}}{Q^{LD}\ \partial P^{LD}}\right)\right] \\
&= \frac{P^1 Q^1}{Y^{LD}}(1 + \eta^{LD}) \\
&= w^1(1 + \eta^{LD}),
\end{aligned}$$

where w^1 is firm 1's share and η^{LD} is the industry level demand elasticity. Putting the components together yields,

$$\eta_{11} = (1 + \eta^{LD}) w^1 \epsilon_1^C + \eta_{11}^C. \tag{3}$$

Equation (3) has an economically intuitive interpretation. The first term measures the "income" effect while the second measures the elasticity holding budgeted income constant. Further, the first term can be decomposed into three effects: P^1 on P^{LD}, P^{LD} on Y^{LD}, and Y^{LD} on Q^1. First, an increase in P^1 holding all other prices constant, will increase P^{LD} by the share of the total market that good 1 represents, w^1. Second, since Y^{LD} is the product of P^{LD} and Q^{LD}, a one percent increase in P^{LD} will increase Y^{LD} one percent directly and decrease Y^{LD} by the upper-level elasticity due to a movement along the upper-level demand curve. Finally, an increase in Y^{LD} will increase the quantity of good 1 demanded according to the lower-level income elasticity.

1. *Upper Level Demand*

The industry demand elasticity for equation (3) is estimated from monthly time series data. Long distance quantity is estimated to be a function of its own price, the prices of local telephone service and telephone sets, income, a time trend and monthly seasonality dummy variables,

$$\begin{aligned} \log Q_t^{LD} &= \eta^{LD} \log P_t^{LD} + \eta^{Loc} \log P_t^{Loc} + \eta^{Set} \log P_t^{Set} + \epsilon \log Income_t \\ &+ \alpha_0\, time + \sum_{\tau=1}^{12} \alpha_\tau\, month_t^\tau + \omega_t. \end{aligned} \tag{4}$$

The quantity of long distance service demanded is expected to fall as price increases, with η^{LD} measuring the industry elasticity. Since local telephone service and telephone sets are complements to long distance service, increases in their prices are expected to lead to a fall in the demand for long distance service, implying that η^{Loc} and η^{Set} should both be negative. The coefficient on income, ϵ, is intended to measure the income elasticity for long distance telephone service and is expected to be positive. The prices of PBXs, computers and modems, which can also be thought of as complements to long distance telephone service, tended to decline over the sample period. Since price series are unavailable for these products, a time trend is introduced to capture this shift in demand, and the coefficient on that time trend, α_0, should be positive. Month dummy variables are intended to account for the seasonality of the demand for telephone calling.

2. *Lower Level Demand*

Budget share regression equations can incorporate the assumptions of two-level budgeting. If the lower-level demand elasticities are constant in the relevant range and only two carriers exist, then equation (1) becomes,

$$\log Q_D^1 = \eta_{11}^C \log P^1 + \eta_{12}^C \log P^2 + \epsilon_1^C \log Y^{LD}.$$

Assuming ϵ_i^C is one,[3] then by adding log P^i to and subtracting the last term from both sides, we get,

$$\log \frac{P^1 Q_D^1}{Y^{LD}} = (1+\eta_{11}^C)\log P^1 + \eta_{12}^C \log P^2.$$

Since Y^{LD} is total industry expenditure, this is the budget share equation. Firm level constrained elasticities are estimated by regressing a firm's revenue market shares against the price of its own service as well as that of its rivals, month seasonality dummy variables and state dummy variables,

$$\log \frac{P_{kt}^i Q_{kt}^i}{Y_{kt}^{LD}} = (1+\eta_{ii}^C)\log P_{kt}^i + \eta_{ij}^C \log P_{kt}^j + \sum_{\kappa=1}^{5} \lambda_\kappa state_{kt}^\kappa + \sum_{\tau=1}^{12} \gamma_\tau month_{kt}^\tau + \mu_{kt}. \qquad (5)$$

Equation (5) is estimated for AT&T and an aggregation of MCI and Sprint. Changes in the relative prices within the industry are expected to induce brand switching causing η_{ii}^C to be negative and η_{ij}^C to be

[3]It is likely that income elasticities do not differ much across long distance companies, implying that the value of ϵ_i^C is one. Data limitations make its estimation problematic. Since quantity is the dependent variable and it is implicit in total long distance expenditures, errors in variables problems could render estimates biased.

positive. Long distance calling demand exhibits sensitivity to seasonal changes and including month dummy variables allows for differences in shifts in demand across brands. State dummy variables are intended to account for idiosyncratic differences in supply and demand across states.

B. Econometric Issues

One of the critical assumptions underlying regression analysis is that all of the regressors are uncorrelated with the error term. If the statistical independence assumption is violated, the parameter estimates are biased and inconsistent. In demand estimation, a frequent cause of statistical dependence is observed prices incorporating the influences of both supply and demand. That is, prices and quantities are determined at the intersection of supply and demand curves. For instance, industry price, one of the regressors in equation (4), and the firms' prices in equation (5), will depend on the level of output through supply relationships. The error terms, ω_t and μ_{kt}, represent the effects on output that are not explained by the modeled demand relationship. Thus, because both the prices and the error terms depend on the output level, they are likely to be correlated.

This problem, of endogenous explanatory variables, can also be thought of as part of the broader problem of "measurement error," that is, of the divergence between the data being observed and the variables being modeled. For example, in demand estimation, the relevant price variable is the price that would prevail if the demand curve did not shift. To the extent that the observed price is affected by a shifting demand curve, it is measured with error. Measurement error in explanatory variables implies correlation between the explanatory variables and the error term, resulting in biased coefficient estimates. The direction and magnitude of the bias is a function of various coefficients and correlations between variables.[4] In equation (5), coefficient bias can result from measurement error in both the own and

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[4]Measurement error in a variable will tend to bias its coefficient toward zero. Measurement error in a different explanatory variable will tend to bias a coefficient in the direction of the product of the (continued...)

competitor prices. Measurement error in the own price will tend to bias the coefficient toward zero. Measurement error in competitor prices will also tend to bias own-price elasticity estimates toward zero (since the correlation between own and competitor prices and the cross-elasticity are both positive and own-price elasticity is negative). Likewise, measurement error in these prices will tend to bias cross-elasticities down (toward zero).

Two general methods of dealing with measurement error are instrumental variables and reverse regressions. The instrumental variables method brings other information to bear in order to recover estimates that are consistent. This method attempts to purge endogenous explanatory variables of their correlation with the error term. Reverse regressions, on the other hand, simply attempt to put bounds on the magnitude of the bias. These regressions switch the dependent and independent variables to generate estimates biased above and below the true parameter value.

1. The Instrumental Variables Method

Since price and quantity are jointly determined, observed prices represent a mixture of demand and supply relationships. Measures of the demand elasticity from direct regression techniques on observed prices will yield biased and inconsistent estimates because the price is endogenously determined. Disentangling demand relationships from supply relationships empirically requires a technique that can distinguish between shifts in the supply curve (movements along the demand curve) and movements along the supply curve (shifts in the demand curve). Price and quantity pairs associated solely with shifts in the supply curve, for instance, will trace out a demand curve whose slope (or elasticity) can be estimated without bias. One method for identifying shifts in the supply curve is to use variables that represent the

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[4](...continued)
correlation between the two variables and the coefficient of the variable with measurement error. The magnitude of the bias will be a function of these various correlations and coefficient values (Maddala (1988) pp. 388-391).

cost of production. The price level that is predicted by these variables would not depend on demand, but instead would reflect only changes in the cost of production. In this manner, the predicted price becomes independent of the error term and the resulting demand estimates are unbiased. In such an application of the instrumental variables technique, the variables representing the cost of production are called the instrument set.

The ability of instrumental variable methods to obtain meaningful demand parameters depends on the ability to find suitable instrumental variables for the endogenous price. The two general requirements are that the instrumental variables be independent of the error term in the demand equation and that they be correlated with the endogenous variable. First, instrumental variables that are themselves functions of the output level will create interdependence between the predicted price and the output level and, thus, between the predicted price and the error term. This reintroduces the problem for which instrumental variables were sought in the first place. Second, correlation between the instrumental variables and price insures that they "explain" some of the variation in the price. That is, they must represent enough of the shifting in the supply curve to provide significant movement along the demand curve. Better predictions of the shifts in the supply curve provide more precise (i.e., smaller variance) estimates of the shape of the demand curve.

A test of bias due to errors in variables can be conducted when instrumental variables are employed. The Durbin-Wu-Hausman test (Hausman (1978)) compares the parameter estimates from two different specifications of a regression model. If the estimates are sufficiently different (in a statistical sense), the specification that relies on the stronger assumptions regarding the data is rejected. In the present context, the assumption that the errors in the variables do not lead to biased estimates (implicit in ordinary least squares (OLS) results) is stronger than the assumption that they might (implicit in instrumental variables results). A Durbin-Wu-Hausman test can also compare parameter results from two different instrumental variable specifications where the instrument sets are different.

2. *Reverse Regressions*

It is possible to place bounds on the true parameter by reversing the direction of the regression. Regressing Y on X when both are measured with error yields a coefficient biased toward zero. Similarly, regressing X on Y will also yield a coefficient biased toward zero. However, the reciprocal of the coefficient of Y from the second regression provides an alternative estimate of the coefficient of X from the first regression. This reciprocal will be biased upward and provides an upper bound on the true parameter,

$$|plim\ \hat{\beta}| < |\beta| < |plim\ 1/\hat{\gamma}|$$

where $\hat{\beta}$ is the estimated coefficient of X in the direct regression, $\hat{\gamma}$ is the estimated coefficient of Y in the reverse regression and β is the true parameter value. This procedure generalizes to multivariate regressions and generates the set of estimates that bound the true parameter value (Klepper and Leamer (1984)). Parameter estimates from reverse regressions are maximum likelihood estimates, and the set of parameter values bounded by these estimates contains the true parameters. As discussed in the previous section, instrumental variable methods, in principle, yield consistent parameter estimates. Yet, because instrumental variable methods may still yield biased coefficient estimates if the instruments themselves are functions of output, reverse regressions can provide additional information about the size of any remaining bias.

C. *The Lerner Index*

The reciprocal of the own-price elasticity, the Lerner index, provides an estimate of the percentage price markup over marginal cost for an unconstrained, profit maximizing firm:

$$L_i \equiv \frac{P_i - MC_i}{P_i} = \frac{1}{|\eta_{ii}|}.$$

This condition is derived from the first order conditions that equate marginal revenue to marginal cost. For larger elasticities (in absolute terms), the marginal revenue curve is closer to the demand curve and the profit maximizing price is closer to marginal cost. In this way, the demand elasticity indicates the extent to which the firm can unilaterally raise prices without suffering a large loss in quantity. This is the extent of the firm's market power. The application of the Lerner index to estimated demand elasticities requires assumptions regarding: the degree to which competitors respond to price changes of rivals, the effect of regulation on AT&T's ability to set prices above marginal costs; and the bias in the implied marginal cost due to the short-run, rather than long-run, nature of the estimated demand elasticities.

The demand elasticity described in equation (3), used to infer the Lerner index, represents the effect of a change in a firm's price on its quantity when competitors' prices are held constant. This is the appropriate elasticity if the firm assumes that its competitors' prices will remain unchanged when it changes its own price, as would be true with the Bertrand conjecture for a differentiated product industry (Carlton and Perloff (1990), pp. 272-276, 308-310). If, however, the firm conjectures that changing its price will induce rivals to adjust their prices (independent of a common change in costs), then this is not the appropriate elasticity. In the extreme case of perfect collusion, price changes by one firm correspond to equal price changes by all others, and the relevant firm-specific elasticity is the industry demand elasticity.

We assume that AT&T will conjecture that its competitors' prices will not change in response to its own price change. First, the non-AT&T carriers ("Other Common Carriers" or "OCCs") have ample capacity with which to expand output. While AT&T's share of fiber optic capacity was 41% in 1992 (Kraushaar (1993)) its share of output was 60% by 1992. This implies that the OCCs have even more capacity for expansion than does AT&T. Second, the average OCC customer is likely to be significantly more price elastic than the average AT&T customer. The average OCC customer demands more than twice the calling volume as demanded by the average AT&T customer.[5] Moreover, since most OCC customers have switched from AT&T at some time, they have revealed themselves to consider OCC service to be a closer substitute for AT&T service than do existing AT&T customers. Third, besides being more price sensitive, OCC customers can choose among a large number of non-AT&T long distance companies whose services are likely to be perceived as good substitutes for each other. Over 500 OCCs other than MCI and Sprint compete in the interstate long distance market (Statistics of Communications Common Carriers (1992)). While most of these firms' operations are confined to reselling service supplied over the facilities of other long distance carriers, nine firms operated facilities in more than 45 states by 1991 (Statistics of Communications Common Carriers (1992)). Moreover, the combined market share of these other OCCs is greater than that of Sprint and the growth in their combined market share since 1988 was greater than that for MCI or Sprint.[6] This suggests that an OCC faces the prospect of customers switching to any of a large number of potential competitors if it attempted to raise its price in response to an AT&T price change. Fourth, the telecommunications industry exhibits characteristics which tend to impede collusion, either tacit or explicit. In addition to the large number of firms, collusive behavior is more difficult to enforce in industries with rapidly changing technologies and, consequently, changing market shares (Stigler (1964)). Long distance telecommunications has experienced an accelerating pace of innovation. Technology innovations include microwave and fiber

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[5]The ratio of a firm's total minutes supplied to the number of its customers represents an index of calling volume per customer. The calculated calling volume index for OCC customers is 2.7 times that for AT&T customers in December, 1987 and 2.0 in June, 1992 (Statistics of Communications Common Carriers (1992)).

[6]Market shares in 1991 were 15.0%, 9.7% and 13.1% and 1988 market shares were 10.3%, 7.2% and 8.0% for MCI, Sprint and all other OCCs respectively (Statistics of Communications Common Carriers (1992)).

optic transmission, asynchronous transfer mode (ATM) and frame relay switching, and software defined network (SDN) and bandwidth-on-demand data communications. Consumer related innovations include magnetic strip calling cards, optional calling plans and "EasyReach 700" service. As long distance companies adopt these innovations to varying degrees, they become better able to serve different niches of the market and collusive arrangements become more difficult to enforce.

Inferring a price-cost markup from a Lerner index requires the assumption that marginal revenue is equated with marginal cost. However, this assumption may not hold for firms, such as AT&T, that face price regulation. With a constrained price, in the short-run the quantity demanded will exceed the unconstrained profit maximizing level and marginal cost will exceed the unconstrained marginal revenue curve. Thus, the price-cost margin under regulation would be smaller than the price-cost margin derived from the profit maximizing assumption implicit in the Lerner index. However, since the firm may be able to respond to regulation, the divergence between marginal revenue and marginal cost will be diminished for two reasons. First, if the firm expects price to be constrained into the future, it can reduce marginal cost to the lower marginal revenue level by reducing investments that maintain quality. Second, if the firm expects price to be unconstrained for some amount of time in the future, the relevant marginal revenue is a weighted average of the constrained and the unconstrained marginal revenues, where the weight is the probability that the constraint will be binding. In the first case, a sub-optimal level of quality is chosen and in the second, the relevant constraint is the expected price-cap over periods when it is binding.

In fact, regulation does not appear to have greatly constrained AT&T's prices, at least since price-caps have been in place. For Basket 1 services, AT&T's price was at its cap only about one-third of the time that price-cap regulation was in effect. Figure 1 shows that the price cap is more likely to be binding just after large changes in the cap brought about by large changes in regulated carrier access prices. I am told that this result could be a reflection of regulatory delay in reviewing AT&T price changes. Thus, even one-third is likely to overstate the fraction of time that the price-cap was binding.

If the estimated elasticities represent less-elastic short-run demand, then the implied Lerner indices will overstate the actual long-run price-cost margin (see figure 2). There are two reasons to expect the estimates to represent short-run elasticities. First, the elasticity estimates are generated with monthly data on price and quantity. In this market, consumers are not likely to fully adjust to a price change until after a year or so. Short-run demand is less elastic because price information is conveyed imperfectly to consumers through advertisements and experiences with monthly bills. Consumers respond to new price information when they become aware of the price change, in some cases months after it actually occurred. Notably, studies estimating long-run industry demand curves for long distance telecommunication often allow current price changes to affect current quantity as well the quantity demanded for a year or so into the future (Taylor (1980), Taylor and Taylor (1993)). Second, the OCC Lerner index values, if construed as long-run estimates, would represent economic rents, i.e., profits from the exercise of market power. While it is possible that OCCs are earning rents, it is likely that most of their implied price-cost margin stems from the upward bias due to the estimation of short-run, and not long-run, demand elasticities.

A measure of the AT&T Lerner index bias generated by the estimation of short-run demand elasticities, instead of long-run elasticities, can be derived from the estimated OCC Lerner index. Under the assumption that long-run OCC firm-specific demand is nearly horizontal, (that is, the OCCs are virtually textbook competitive firms), their long-run price-cost margin is very small. The FCC considered "competition in business services to be thriving," from which can be inferred that the FCC considered AT&T's ability, let alone the OCCs' ability, to set prices above marginal cost for business services to be negligible (Federal Communications Commission (1991)). Since some of these business customers are long distance resellers, the ability of the OCCs to set prices significantly above marginal costs to residential customers appears quite limited. In this case, almost all of the estimated OCC Lerner index represents a measure of the bias. If the amount of the bias is the same for AT&T and the OCCs, then the actual price-cost margin for AT&T can be approximated by,

$$\begin{aligned}\hat{L}_{LR}^{ATT} &= \hat{L}_{SR}^{ATT} - \hat{L}_{SR}^{OCC} \\ &= \frac{1}{\left|\hat{\eta}_{SR}^{ATT}\right|} - \frac{1}{\left|\hat{\eta}_{SR}^{OCC}\right|},\end{aligned}$$

the difference between the estimated price-cost margins for AT&T and the OCCs.

IV. Data Description

This section describes the basic data employed to estimate long distance telephone demand relationships described by equations (4) and (5). The upper level demand estimation, equation (4), uses national time series data for the period July 1986 to August 1991. The lower level demand estimations, equation (5), uses monthly data for the years 1988 to 1991 for five states. Instrumental variables are employed to identify structural demand parameters in both estimations. This section describes the data used, focusing primarily on the lower level estimation.

A. Upper Level Estimation

For the upper level demand estimates, equation (4), national data were collected from various sources on output, prices and income. The total number of minutes of interstate calling is used as the industry output. These data come from National Exchange Carrier Association (NECA) reports to the FCC. The CPI prices for interstate long distance and local service, and the PPI for telephone sets were used as price variables. Per capita personal income was used as the measure of income. All prices and income data are deflated by the CPI for all goods and services.

The price of long distance is treated as endogenous, so instrumental variable techniques are necessary. Instrumental variables that are available are the PPI indices for transmission and digital switching equipment and the wages of telecommunications workers. All of these represent prices of key inputs into the production of long distance services and, thus, should represent shifts in the supply curve. They will be correlated with the quantity demanded only to the extent that the long distance industry represents a significant portion of the total demand for the individual factors and these markets have upward (or downward) sloping supply curves. While the long distance industry does account for a large fraction of these equipment markets, there is no evidence on the slope of the supply curves.

B. Lower Level Estimation

The principal data used in the estimation of lower level demand, equation (5), are interstate carrier access usage and expenditure information for AT&T and the Other Common Carriers (OCCs).[7] The carrier access usage information available is for switched and special access purchased by AT&T, MCI, Sprint and an aggregation of the other long distance companies. These data span five states and each month from January 1988 through December 1991 for a total of 240 observations. Interstate toll service is the focus of this study both because these data were the most accessible and because this is one of the most important segments of the market.

1. Demand Variables

A number of relevant variables are available. For each state, month and long distance company, the variables available are the number of minutes and dollar expenditure on interstate switched access and the number of lines and dollar expenditure on interstate special access. Since these data are obtained

[7]These data are used under a nondisclosure agreement with Southwestern Bell Telephone Co. and are not publicly available.

from billing information, they should reflect actual purchases accurately. The number of switched access minutes measures the quantity of long distance service demanded. The quantity is the sum of both the number of outgoing and incoming minutes. Long distance companies have increasingly moved their larger customers to special access and facilities bypass. If special access usage grew faster for the OCCs than for AT&T, market shares based on switched access alone would underestimate the OCC market penetration and will tend to bias own-price elasticities downward. However, the market share based solely on switched access more accurately represents Basket 1 services. Dividing interstate switched access expense by interstate switched minutes yields an average price for switched access per minute. Dividing interstate special access expense by the interstate number of lines yields an average price per special access line.

The price of long distance service for different firms is of key importance to the estimated results, and is the weakest data element. Long distance price variables were constructed from price information in tariffs filed at the FCC. AT&T, MCI and Sprint submit rate schedules to the FCC when they change their rates. These schedules list prices by time of day (day, evening and night), first or additional minute and distance of the call (there are twelve different mileage bands). Since the quantity variable aggregates calls over all of these dimensions, the relevant price is a weighted average over all of these dimensions. However, the appropriate weights can only be approximated and some assumptions must be made regarding the relative use along these dimensions.

Time of day, duration and distance weights were computed using intraLATA toll information and some simplifying assumptions. The average duration and the fraction of calls by day, evening and night were available for local telephone toll service by state. Applying these weights to the interstate data assumes comparability between the shorter distance intraLATA and the longer distance interstate calling patterns. The relative weights for the separate mileage bands were computed in an admittedly *ad hoc* way. A so called "gravity" model of telephone traffic flows was employed to calculate the expected number of calls flowing between two points as proportional to the product of the "mass" of the two locations divided by the square of the distance between the two locations. The expected flows were calculated for each of the 3187 counties in the U.S. to each county of the states in the dataset using the counties' geographic center to compute distances and its 1991 population for its mass. The individual county flows for a state are aggregated into the mileage bands.[8] The price is averaged over mileage bands using the aggregated state flows as weights.

2. *Potential Measurement Errors in the Long Distance Prices*

Due to the many assumptions inherent in the construction of the price variable, it is appropriate to check it against other sources. One price series available for comparison is the AT&T price index reported to the FCC. As part of the filing requirements for price-cap regulation, AT&T has reported price indices for different baskets of services since April of 1989. The price index for Basket 1 Services represents an independent measure of the long distance prices constructed above. Figure 3 displays the constructed long distance prices for AT&T and the OCCs in Texas and the Basket 1 index for AT&T.[9] It appears as though the constructed AT&T price closely follows the Basket 1 index. The gradual deviation between the two series may be accounted for by smaller price reductions in the international and calling card calls, which are included in the Basket 1 price index but excluded from the constructed price.

Discounts from posted prices are another potential problem with the constructed prices. Programs like AT&T's Reach Out America, MCI's Friends and Family and Sprint's Most tend to offer a percentage discount off the posted prices. If discounted prices vary more than posted prices, then changes in posted

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[8]Bob Evett and Equifax National Decision Systems are gratefully acknowledged for the use of these data.

[9]The other states in the sample yield similar results. Texas was chosen because it represents about half of all the long distance in the sample.

prices will understate actual price changes and estimated price elasticities will overstate true price elasticities. Figure 4 confirms that AT&T's Residential and Small Business and Reach Out America indices diverge slightly over time. However, the slight divergence suggests that this source of measurement error is small. The same is likely to be true for the OCC price.

Another measurement error in the OCC price results from the exclusion of firms other than the two largest, MCI and Sprint. Price data were not collected for these other firms because the largest represents less than 1% of industry revenues and because quantity information was available only for the aggregation of these firms. The combined market share of these firms has grown from about 7% to 13% between 1988 and 1991. To the extent that these firms' services are substitutes for AT&T's and these smaller firms prices are uncorrelated with MCIs' and Sprints', AT&T's estimated own-price elasticity should be biased toward zero. However, the small differences between the MCI and Sprint prices relative to their difference from the AT&T price suggests that the OCCs' prices are highly correlated with each other and that this bias should be small.

3. Instrumental Variables

As noted above, inconsistent coefficient estimates due to errors in variables can be overcome with the use of suitable instrumental variables. The constructed firm-specific long distance prices are likely to contain errors because of both supply and demand simultaneity and the assumptions inherent in their construction. Instrumental variables are required to predict supply prices and purge measurement errors. Moreover, in order to estimate firm-specific price elasticities, firm-specific instruments are needed so that shifts in the supply curve for a particular firm are independent of shifts in the supply curves for other firms. Factor prices could be suitable instrumental variables if they are unique to each firm. If, however, a factor represents a commodity good to all firms (e.g., raw materials), then changes in the factor price are likely to induce similar shifts in supply for all firms in the industry.

The available firm-specific factor prices include the cost of capital and the average prices of carrier access. These factor prices are added to the set of instrumental variables used in the upper level. Measures of the cost of debt are derived from Moody's yield to maturity calculations on outstanding debt for each of the largest three long distance companies. A bond's yield to maturity is deflated by the yield to maturity for a similarly lived government bond in order to adjust for changes in expected inflation. Finally, a firm's outstanding bonds are aggregated into a single yield to maturity using their face value as weights. The cost of capital can be expected to be unique to each firm, correlated with price and uncorrelated with the error term in the demand equation. First, the cost of capital depends largely on the riskiness of the firm borrowing the funds. In the long distance market, AT&T's capital costs reflect a relatively risk free firm, while MCI pays a relatively high interest rate on its junk bond debt. Second, since the firms in this industry are relatively capital intensive, changes in their cost of capital are likely to induce relatively large price changes. Third, the cost of capital is likely to be independent of the output level and, thus, the error term.

While carrier access prices may be both unique for each long distance company and highly correlated with long distance price, they may also be correlated with output and, thus, the error term. Firms differ in their carrier access purchases mainly because of the degree to which they integrate into the distribution of telephone calls. When a sufficient volume of calling for a long distance company originates or terminates in a particular area, the long distance company will extend its network into the area and thus reduce its purchase of access from the local telephone company.[10] Thus, average switched access prices will depend on the location and the calling patterns of a long distance company's customers.

[10]Long distance companies typically terminate their networks near the centers of metropolitan areas. Calls to and from outlying areas are transported to the long distance network by local telephone company at a charge that increases with distance. When the volume of traffic for the outlying area develops sufficiently, a long distance company will extend its network to the area. This occurs when the cost savings from reduced expenditures on local telephone company transport is greater than the cost of extending the network.

More geographically concentrated customers and calls will lead to more backward integration, lower expenditures for switched access and lower total costs. Likewise, average special access prices tend to be lower in areas of more densely located customers and calls because less costly, higher capacity lines can be used. Changes in carrier access rates are highly correlated with long distance prices, explaining much of the decreases in prices (Taylor (1991)). However, there is evidence that carrier access prices fall as more is demanded (Parsons and Ward (1993)). Thus, using carrier access prices as instruments may reintroduce correlation between long distance prices and the error term in the demand equation.

4. *Some Tests of the Instrumental Variables*

While the focus of this paper is on demand estimation, one way to evaluate the effectiveness of the demand instruments is to estimate supply relationships. This analysis can also provide an estimate of the effect of price-cap regulation on AT&T's costs. Price-caps, which replaced rate-of-return as the regulatory scheme for AT&T midway through the sample, may provide AT&T stronger incentives to reduce costs (Liston (1993)). In general, the supply curve is expected to be quite elastic given the relatively large fixed costs relative to variable costs in the industry.[11] Supply relationships are estimated with the firm specific data using the equation,

$$\log P_{kt} = \psi\, cap_{kt} + \theta \log Q_{kt} + \sum_{l\in L} \phi_l \log w_{kt}^{l} + \sum_{\kappa=1}^{5} \beta_\kappa state_{kt}^{\kappa} + \nu_{kt}. \tag{6}$$

Cap is a dummy variable whose value is one during the time that AT&T was regulated under the price-cap regime as opposed to the rate-of-return regime. The w^ls, the factor input prices, are the PPI indices for transmission and digital switching equipment, the wages of telecommunications workers, the yield to

[11]In fact, Huber, et al. (1993) contend that the technology is developing into that of a natural oligopoly due to scale economies in transmission.

maturity on corporate bonds, and the average prices for switched and special access. The instruments for quantity are income and month dummy variables.[12]

Estimation results for equation (6) are reported in table 1. First, as expected, supply curves appear to be flat. Still, coefficient estimates not significantly different from zero are likely due to the meager instruments available for the quantity demanded. Indeed, the negative coefficients for minutes of use could be a demand relationship picked up because both output and income, an instrumental variable, are correlated through a time trend in both variables. Second, there is evidence that the movement toward price-cap regulation lowered AT&T's costs. The price-cap coefficient is negative for both AT&T and the OCCs but is significant for AT&T only. This conforms to the hypothesis that price-cap regulation is a more efficient form of regulation for long distance telephone service and with other empirical results (Mathios and Rogers (1989, 1990), Kaestner and Kahn (1990)). Since the OCCs are not subject to regulation, the only effect of price-cap regulation on their prices would be through more vigorous competition with a more cost-efficient AT&T.

The third result is that the industry-wide and firm-specific factor input prices are relatively good explanatory variables for the price of long distance service. Increases in the prices of inputs common to all firms -- switching equipment, transmission equipment and labor -- increase the output price for both AT&T and the OCCs, with coefficient magnitudes and confidence levels differing across firms. The yield to maturity on corporate bonds, a measure of the cost of capital, is significant only for the OCCs. This result is reasonable since much of MCI's debt is in the form of junk bonds whose prices are more variable than the bonds issued by AT&T. Note also that the estimated coefficients of switched and

[12]Price-cap regulation of AT&T could render its supply price censored at the price-cap, suggesting that Tobit estimates of equation (8) are more appropriate. As mentioned above, for Basket 1 services, AT&T's price was at its cap about one-third of the time that price-cap regulation was in effect. Also, periods in which the cap was binding are possibly the result of regulatory delay. Since, in these cases, the price cap may actually be a floor and not a ceiling, attempts to account for censoring are not reported.

special access prices are all positive and significant. The estimated standard errors are quite small, indicating that these input prices should be good proxies for firm-specific shifts in supply, which are needed in the demand estimation.

V. Demand Estimation Results

The results of the demand estimations are presented in this section. In the upper level regressions, the results are quite similar to estimates presented in other research. Specifically, the commonly accepted industry demand elasticity of -0.65 cannot be rejected. In the lower level regressions, firm-specific demand elasticities for both AT&T and the OCCs are found to be sensitive to assumptions regarding the errors in the variables. Carrier access prices can be rejected as suitable instrumental variables due to their endogeneity with output. The elasticity estimates resulting from the restricted instrument set (i.e., one without carrier access prices) provide a smaller range of estimates. Lower bound estimates of short-run own-price demand elasticities are -2.9 for AT&T and -6.6 for the OCCs. While consumers are not likely to fully adjust to price changes until after a year or so, these estimates indicate that demand is fairly elastic even in the short-run.

Estimation results for the industry level demand estimation, equation (4), are reported in table 2. Columns (1) and (2) exclude the time trend and provide evidence that local service and telephone sets are strong complements with long distance services. Columns (3) and (4) include a time trend to capture an exogenous shift in demand (e.g., the growth of data and facsimile transmissions). The resulting cross-price elasticities are smaller and are now insignificant at standard levels. Where Hausman, Tardiff and Belefante (1993) find significant cross-elastic effects from long distance prices on local service penetration rates, the converse cross-elastic results are mixed here. Estimated own-price elasticities are significant and similar to those reported elsewhere (Taylor and Taylor (1993), Taylor (1980)). In fact, the commonly accepted value of -0.65 can only be rejected in column (1).

Table 3 reports two-stage least squares (2SLS) regression results for the lower level demand, equation (5), under various assumptions regarding the errors in variables.[13] Because Durbin-Wu-Hausman tests always reject OLS results in favor of instrumental variables results, only the latter are reported. The left panel uses all of the instruments and the right panel uses all instruments except the carrier access prices. Since carrier access prices can be correlated with the quantity demanded, results that rely on them may still be biased. In each panel, the results from the direct estimation of the market share regressions, as well as the results from the estimation of the reverse price regressions, are reported. Coefficient estimates from the reverse regressions are not directly reported, but are used to compute parameter estimates comparable to those obtained from the direct regression. The top panel reports the results for AT&T demand and the bottom panel reports those for the OCCs.

Coefficient estimates vary widely depending on the errors in variables assumptions made regarding the data. When all of the instruments are used, the estimate on AT&T's own-price elasticity varies from -1.16 to -5.87. Bias toward zero is confirmed by reverse regression estimates that are larger (in absolute terms) than those from the direct regression. The range of coefficient estimates shrinks to -2.15 to -4.68 when the instrument set excludes carrier access prices. Likewise, the range of own-price estimates for the OCCs collapses from between -3.09 and -13.95 using all instruments to between -5.73 and -9.27 using the restricted instrument set. These results are consistent with the conjecture that carrier access prices are unsuitable as instruments. Indeed, in all cases, Durbin-Wu-Hausman tests reject the hypotheses that the coefficient estimates are the same using either instrument set.

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[13]While applying a Tobit regression to the first stage to account for possible censoring at the price-cap does change the estimated coefficients in the first stage, the results for the second stage are virtually unchanged.

Unconditional own-price elasticities are now constructed using equation (3). These elasticities and their associated Lerner indices are reported in table 4 assuming an industry demand elasticity of -0.65 and revenue market shares of 0.647 for AT&T and 0.269 for the OCCs.[14] For example, AT&T's own-price coefficient of -2.15 from the direct regression using the restricted instrument set yields an estimated own-price elasticity of -2.92 and a Lerner index of 0.337. Under the same assumptions, the OCC own-price coefficient of -5.73 translates into an own-price elasticity of -6.64 and the Lerner index is 0.151. That is, AT&T's price markup over marginal cost is estimated to be about 33.7% of its price, while the OCC's is 15.1%.

VI. Potential Deadweight Loss Calculations

As noted above, firm-specific demand elasticities imply price markups over marginal cost via the Lerner index. Also noted above, the estimated elasticities and their associated Lerner indices are likely to represent short-run, and not long-run relationships. This implies that the estimated markup over marginal cost is biased upward. To calculate long-run elasticities and Lerner indices for AT&T, the size of the bias introduced by short-run demand elasticities must be accounted for. Under the assumption that the OCCs are earning no economic rents at all, their Lerner index represents a measure of this bias for the OCCs.[15] If the amount of the bias is the same for AT&T and the OCCs, then the actual price-cost margin for AT&T can be approximated by the difference between the estimated price-cost margins for AT&T and the OCCs. This provides an upper bound estimate of the price markup over long-run marginal cost of 18.6% (33.7% - 15.1%) using the estimated results from the direct regression and the

[14]These shares do not add up to one because the OCC share excludes long distance companies other than MCI and Sprint.

[15]If the OCCs are in fact earning some economic rents, then this methodology will tend to overstate the Lerner index bias caused by the estimation of short-run demand elasticities.